FAST VIGNETTING CORRECTION AND COLOR MATCHING FOR PANORAMIC IMAGE STITCHING

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ABSTRACT

When images are stitched together to form a panorama there is often color mismatch between the source images due to vignetting and differences in exposure and white balance between images. In this paper a low complexity method is proposed to correct vignetting and differences in color between images, producing panoramas that look consistent across all source images. Unlike most previous methods which require complex non-linear optimization to solve for correction parameters, our method requires only linear regressions with a low number of parameters, resulting in a fast, computationally efficient method. Experimental results show the proposed method effectively removes vignetting effects and produces images that are highly visually consistent in color and brightness.

Index Terms— color correction, vignetting, panorama, image stitching

1. INTRODUCTION

A popular application of image registration techniques is to stitch together multiple photos into a panorama [1][2]. This allows wide angle images (up to 360°) to be created from multiple photos taken with a normal camera. Panoramic image stitching has been extensively studied in the literature [2] and there are also several commercial software programs for creating panoramas.

When two images are aligned, there are almost always visible seams due to mismatches in the brightness and color between images (Fig 1). There are several causes of these seams, such as registration errors, exposure differences, vignetting [3] (radial falloff towards the edges of an image) and variable white balance.

To prevent visible edges in the final panorama, blending techniques are used to make transitions between images smooth. Popular methods include multi-band blending [4][1] and gradient domain blending [5]. While these techniques do remove visible seams, they do nothing to remove global color differences. Therefore using blending techniques alone can result in unnatural looking panoramas, as seen in Figure 1 (right).

Fig. 1. Two images showing severe color mismatch aligned with no blending (left) and multi-band blending [1] (right)

To compensate for brightness/color differences between images in panoramas, several techniques have been proposed [1],[6]-[9]. The simplest of these is to multiply each image by a scaling factor [1]. A simple scaling can somewhat correct exposure differences, but cannot correct for vignetting, so a number of more sophisticated techniques have been developed.

A common camera model is used in most previous work on vignetting and exposure correction for panoramas [6]-[9]. A scene radiance value L is mapped to an image pixel value I, through:

$$I = f(eV(\mathbf{x})L) \qquad (1)$$

In equation (1), e is the exposure with which the image was captured, and $f(E)$ is the cameras response function, which in general can be a non-linear function. The pixel value I represents a red, green or blue sample. $V(\mathbf{x})$ is the vignetting function which is dependent on the position of the pixel in the image ($\mathbf{x}$). $V(\mathbf{x})$ is one at the image's optical center and it decreases towards the edges. The irradiance observed by the image sensor at location $\mathbf{x}$ is $E = eV(\mathbf{x})L$. With an estimate of the exposure, and models for the camera response $f(E)$ and the vignetting $V(\mathbf{x})$, the scene radiance can be recovered from the measured pixel value as:

$$L = \frac{g(I)}{eV(\mathbf{x})} \qquad (2)$$

where $g(I)$ is the inverse of the camera response function. Once the radiance values are found, each image can be rendered with a common exposure and no vignetting (i.e. $V(\mathbf{x})=1$) with equation (1), which should correct color mismatches between images.

In [6], the camera response function is modeled as a gamma curve and vignetting is modeled as $\cos^4(d/f)$, where d

is the radial distance between the pixel and the center of the image and f is the focal length. In the [7] authors generalize the camera response model to be a polynomial.

An influential method for removing vignetting and exposure differences is proposed by Goldman and Chen in [8], which uses an empirical camera response model together with a polynomial model for vignetting. Specifically a 6th order even polynomial is used:

$$V(d) = 1 + \alpha_1 d^2 + \alpha_2 d^4 + \alpha_3 d^6 \qquad (3)$$

In (3), the α values are weights adjusted to make the polynomial fit the observed vignetting.

Another method based on Goldman and Chen work is proposed in [9]. A white balance factor is introduced, so that $I = f(eV(\mathbf{x})Lw_c)$. The optimization problem is reformulated so that a single non-linear optimization is done with the Levenberg-Marquardt method rather than the iterative optimization method used in [8].

While methods for removing vignetting and color differences between images do greatly reduce seams, they do not completely remove them, so blending techniques are still required [6]-[9]. Even if the color of images could be perfectly matched, blending would still be necessary to disguise small alignment errors and scene movement [2].

In previous work that corrects for both vignetting and exposure differences, non-linear optimization is used [6]-[9]. Non-linear optimization methods have considerably higher complexity than linear ones, and therefore may take a long time to run [8], and may have problems with convergence [7].

In this paper we proposed a vignetting correction and color matching method that uses only linear least-squares regression. Linear regression has far lower complexity than non-linear optimization and has no problems with convergence since the global optimum can be determined in closed form. In order to use simple linear regression, we correct vignetting with an additive term, and match the color between two images with a 2nd order polynomial. Experiments show the proposed method effectively corrects for vignetting, exposure and white balance differences between images. When combined with blending methods the proposed method gives panoramas with no visible mismatch between images.

The rest of this paper is organized as follows. The proposed method is described in section 2. Experimental results are presented in section 3 and conclusions are given in section 4.

2. PROPOSED METHOD

We assume that we have two images, $I_1(x,y)$ and $I_2(x,y)$ that have been registered so that an overlapping area has been identified (in our experiments we align images using autostitch [1]). Our goal is to correct vignetting in both images and make the color of I_1 match that of I_2 (so that I_2 is

the image used as the color reference). We will first describe the method for correcting two images, and then describe how it is extended to a greater number of images.

Vignetting correction is usually done by dividing the irradiance by the estimated vignetting attenuation, as in equation (2). In order to use a simple linear regression we would like to compensate for vignetting with an additive term. Define E_0 to be the irradiance that would be measured by the sensor if there were no vignetting ($E_0 = eL$). The drop in irradiance due to vignetting using the polynomial model (3) is:

$$\begin{aligned} \Delta E_{vig} &= E_0 - E \\ &= E_0 - E_0\left(1 + \alpha_1 d^2 + \alpha_2 d^4 + \alpha_3 d^6\right) \\ &= -E_0\left(\alpha_1 d^2 + \alpha_2 d^4 + \alpha_3 d^6\right) \end{aligned} \qquad (4)$$

Since an image pixel value is proportional to the irradiance, we can say that the corresponding drop in the image sample will be approximately:

$$\Delta I_{vig} = -I\left(\alpha_1 d^2 + \alpha_2 d^4 + \alpha_3 d^6\right) \qquad (5)$$

Note that the vignetting model of equation (5) would be equivalent to the model in equation (4) if the cameras response were linear. In image 2, we will only correct vignetting, so applying equation (5) the corrected image is calculated with:

$$I_{2,cor} = I_2 + I_2\left(\alpha_1 d_2^2 + \alpha_2 d_2^4 + \alpha_3 d_2^6\right) \qquad (6)$$

In image 1, we have to correct both for vignetting and for exposure and white balance differences between images. To do this we propose to use a 2nd order polynomial to model a transfer function to render a pixel in image 1 with the exposure and white balance of image 2. Hence the function we use for correcting vignetting in image 1 and making its color match image 2 is:

$$I_{1,cor} = a_1 I_1 + a_2 I_1^2 + a_3 + I_1\left(\alpha_1 d_1^2 + \alpha_2 d_1^4 + \alpha_3 d_2^6\right) \qquad (7)$$

The optimal weights a_i and α_i that will make the images consistent will be estimated from matching points in the overlapping region. Vignetting affects all color channels equally, so the weights for vignetting should be common to all three channels (R, G, and B), but the other weights are different for each channel.

The corrected values of image 1 calculated with (7) should equal the corrected values of image 2 calculated with (6). Applying this to the R, G and B channels gives the set of equations:

$$\begin{aligned} R_2 + \alpha_1 d_2^2 R_2 + \alpha_2 d_2^4 R_2 + \alpha_3 d_2^6 R_2 &= a_{R1}R_1 + a_{R2}R_1^2 + a_{R3} + \alpha_1 d_1^2 R_1 + \alpha_2 d_1^4 R_1 + \alpha_3 d_1^6 R_1 \\ G_2 + \alpha_1 d_2^2 G_2 + \alpha_2 d_2^4 G_2 + \alpha_3 d_2^6 G_2 &= a_{G1}G_1 + a_{G2}G_1^2 + a_{G3} + \alpha_1 d_1^2 G_1 + \alpha_2 d_1^4 G_1 + \alpha_3 d_1^6 G_1 \\ B_2 + \alpha_1 d_2^2 B_2 + \alpha_2 d_2^4 B_2 + \alpha_3 d_2^6 B_2 &= a_{B1}B_1 + a_{B2}B_1^2 + a_{B3} + \alpha_1 d_1^2 B_1 + \alpha_2 d_1^4 B_1 + \alpha_3 d_1^6 B_1 \end{aligned} \qquad (8)$$

After both images have been warped into the coordinates of the final panorama, there will be a region

where the images are overlapping. Define vectors of the red, green and blue samples in the overlapping region as $\mathbf{R_1}$, $\mathbf{G_1}$, $\mathbf{B_1}$ and $\mathbf{R_2}$, $\mathbf{G_2}$, $\mathbf{B_2}$. The equations in (8) can be written for these vectors of matching points as:

$$\begin{bmatrix} \mathbf{R_2} \\ \mathbf{G_2} \\ \mathbf{B_2} \end{bmatrix} = \mathbf{\Psi a} + \mathbf{\varepsilon} \qquad (9)$$

with $\mathbf{a}$ and $\mathbf{\Psi}$ defined as:

$$\mathbf{a} = [a_{R1} \; a_{R2} \; a_{R3} \; a_{G1} \; a_{G2} \; a_{G3} \; a_{B1} \; a_{B2} \; a_{B3} \; \alpha_1 \; \alpha_2 \; \alpha_3]^T$$

$$\mathbf{\Psi} = \begin{bmatrix} \mathbf{R_1} & \mathbf{R_1^2} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{R_1 d_1^2} - \mathbf{R_2 d_2^2} & \mathbf{R_1 d_1^4} - \mathbf{R_2 d_2^4} & \mathbf{R_1 d_1^6} - \mathbf{R_2 d_2^6} \\ 0 & 0 & 0 & \mathbf{G_1} & \mathbf{G_1^2} & 1 & 0 & 0 & 0 & \mathbf{G_1 d_1^2} - \mathbf{G_2 d_2^2} & \mathbf{G_1 d_1^4} - \mathbf{G_2 d_2^4} & \mathbf{G_1 d_1^6} - \mathbf{G_2 d_2^6} \\ 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{B_1} & \mathbf{B_1^2} & 1 & \mathbf{B_1 d_1^2} - \mathbf{B_2 d_2^2} & \mathbf{B_1 d_1^4} - \mathbf{B_2 d_2^4} & \mathbf{B_1 d_1^6} - \mathbf{B_2 d_2^6} \end{bmatrix}$$

$$(10)$$

The $\mathbf{\varepsilon}$ vector in (9) is the error between the corrected image samples that we want to minimize. The vector $\mathbf{a}$ which minimizes the squared error between the corrected RGB values of image 1 and the matching RGB values of image 2 can be obtained with a standard linear least-squares regression:

$$\mathbf{a} = \left(\mathbf{\Psi}^T \mathbf{\Psi} \right)^{-1} \mathbf{\Psi}^T \begin{bmatrix} \mathbf{R_2} \\ \mathbf{G_2} \\ \mathbf{B_2} \end{bmatrix} \qquad (11)$$

After the parameters vector is calculated with (11), the final corrected version of image 1 is calculated with (7), and the corrected version of image 2 is calculated with (6).

After correcting these first two images, more images can be corrected using those that have already been corrected. Suppose we are correcting image j which has an overlapping area with image k that has already been corrected. The corrected version of image j will be generated with (8), which should equal the already known corrected pixels of image k:

$$I_{k,cor} = a_1 I_j + a_2 I_j^2 + a_3 + I_j \left(\alpha_1 d_j^2 + \alpha_2 d_j^4 \right) \qquad (12)$$

Based on (12), a set equations equivalent to those of (8) can easily be derived (but without the vignetting terms on the left hand side of each equation). Another least squares regression is done as in equation (11), only with $\mathbf{\Psi}$ modified

slightly to account for the fact that there is no vignetting in the already corrected image.

Image registration is usually not accurate to within a pixel, so matching points near edges are less reliable than those in flat image regions. Therefore we do not use matching points that have a high gradient value in either image. We calculated the gradient magnitude at each pixel as:

$$G(x, y) = \left| I(x+1, y) - I(x-1, y) \right| + \left| I(x, y+1) - I(x, y-1) \right| \quad (13)$$

If the gradient is above a threshold (we use 10 in our experiments) the matching points are not used in the regressions for calculating the correction parameters.

To lower the computational cost of performing the regressions a small subset of the pixels in the overlapping region can be used in each regression. In our experiments, we have used 200 matching points in each regression, sampled uniformly in spherical coordinates in the overlapping region.

3. RESULTS

Sample panoramas before and after color correction are shown in Figures 3 and 4. Each panorama is obtained by blending the images with a checkerboard pattern, in order to highlight color differences between images. We compare our proposed method against the method of Goldman and Chen [8]. Since our goal is to provide visually pleasing panoramas, only subjective comparisons are made.

Figure 3 shows images with large exposure differences, causing the images on the right-most image of the panorama to look much darker then the left-most image. After correcting the images with Goldman's method the checkerboard pattern is still visible in the grass and the image on the right is still visibly darker then the one on the left (Fig. 3b). These problems are not visible on the images corrected with the proposed method (Fig. 3c).

Figure 4 shows an example with pronounced vignetting in the sky. While Goldman's method reduces the appearance of seams (Fig. 4b), they are even less visible after applying the proposed method (Fig. 4c). In addition to providing better color matching between images, the proposed method requires only linear regressions on a

(a)   (b)   (c)

Fig. 3. Green lake panorama (a) Original images, (b) Corrected with Goldman's method [8], (c) Proposed correction method

relatively small number of samples, whereas Goldman's method [8] requires a much more complex non-linear optimization.

Two more example panoramas are shown in Figures 5 and 6. Before correction the color mismatch between images is highly visible, whereas after correction only minor seams are noticeable. Applying blending techniques [4][5] will easily remove the remaining seams, which are mostly due to small alignment problems rather than color mismatch.

4. CONCLUSIONS

In this paper we propose a method for correcting vignetting and color differences between images being stitched together to form panoramas. Unlike previous methods which use complex non-linear optimization to solve for the correction parameters, our proposed method uses only linear least squares regressions with a lower number of parameters. This makes our proposed method fast, and avoids problems with convergence that can be encountered with non-linear optimization. Results show that our method effectively corrects for vignetting, exposure and white balance differences between images, producing panoramas with negligible color mismatch between images.

5. REFERENCES

[1] M. Brown and D. Lowe. "Automatic Panoramic Image Stitching using Invariant Features," International Journal of Computer Vision, vol. 74, no. 1, pp. 59-73, 2007.

[2] R. Szeliski. Image alignment and stitching: A tutorial. Technical Report MSR-TR-2004-92, Microsoft Research, Dec. 2004.

[3] Y. Zheng, S. Lin, S.B. Kang, "Single-Image Vignetting Correction," Proc Computer Vision and Pattern Recognition (CVPR 2006), vol.1, no., pp. 461-468, 17-22 June 2006

[4] P. Burt and E. Adelson, "A multiresolution spline with application to image mosaics," ACM Transactions on Graphics, vol. 2, no 4, pp. 217–236, 1983.

[5] A. Levin, A. Zomet, S. Peleg, and Y. Weiss, "Seamless image stitching in the gradient domain," in Proc. European Conf. Computer Vision (ECCV 2004), pp. 377–389.

[6] D. Hasler and S. Süsstrunk, "Color Handling in Panoramic Photography," Proc. IS&T/SPIE Electronic Imaging 2001: Videometrics and Optical Methods for 3D Shape Measurement, Vol. 4309, pp. 62-72, 2001.

[7] D. Hasler and S. Süsstrunk, "Mapping colour in image stitching applications," Journal of Visual Communication and Image Representation, vol. 15, num. 12, pp. 65-90, 2004.

[8] D. Goldman and J. Chen, "Vignette and Exposure Calibration and Compensation," Proc. IEEE Int'l Conf. Computer Vision, pp. 899-906, Oct. 2005.

[9] P. d'Angelo, "Radiometric alignment and vignetting calibration," Proc. Camera Calibration Methods for Computer Vision Systems, Mar. 2007.

Fig. 4. Skyline panorama. (a) Original images, (b) Correction with Goldman's method [8], (c) Proposed correction method

Fig. 5. Sunset panorama. Original images (top) and after proposed correction (bottom)
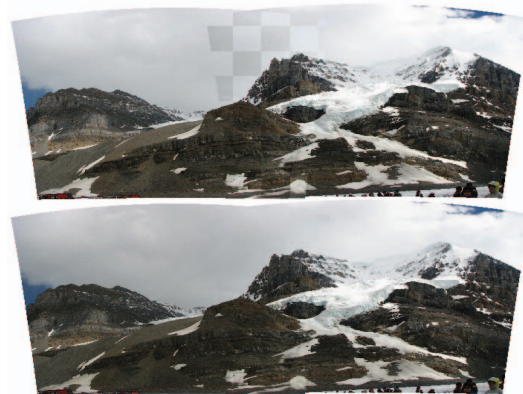

Fig. 6. Mountain panorama, original images (top) and after proposed correction (bottom)